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Combining Genetic with RDPTA Algorithm for the Prolonging of the Lifetime of Wireless Sensor Networks

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Abstract: *In this paper, we try to prolong the lifetime of the wireless sensor with using genetic algorithm and one of the neural network techniques which is named as Two dimensional R-category Discrete perception Training Algorithm (RDPTA). In this work firstly, in order to get accurate clustering in nodes, which is appropriate for solving the problems locally, all the nodes are clustered with using new function in genetic algorithm. Secondly, in order to make nodes to learn from obtained part of genetic algorithm, we used the RDPTA algorithm, which is the decision-maker to select a cluster head. In order to make a decision the RDPTA algorithm, consider x_1 and x_2 variables as the Energy and Distance of nodes respectively, and also as ranks of best-selected cluster head consider class 1 and class 2 and class 3 as very good, good and bad respectively. Our results confirm that our proposed algorithm relatively outperforms two Leach and Leach-c algorithms. The proposed algorithm is able to insert new nodes in the each part of space and this node is performed based on the RDPTA of part.*

Keywords: *Genetic algorithm, Perceptron Training, Life Time, Wireless Sensor Network*

1. Introduction

Wireless sensor networks are one of the new issues, which have different challenges such as energy consumption and network coverage. Most research focused on the improvement of the lifetime of the wireless sensor networks. The inherent limited battery is one of the problems, which is inevitable. Most of the papers proposed different points of view and techniques to solve the problem. LEACH is the well-known method to prolong the lifetime of wireless networks, which uses its clustering approach and multi hop communication [1].

In one of the papers there is improvement of the lifetime of the wireless sensor networks which increases alive nodes in the network by using a different approach to selecting cluster head [2]. Energy Based Clustering Self organizing map (EBCS) is another approach, this new protocol clusters sensor nodes is based on multiple parameters [3].

Another paper compares with two important clustering protocols, namely LEACH and LEACH-C [5]. Also, another paper investigates the problem of uniform node distribution and shows its incapability to solve the problem of whole energy of nodes and tries to balance lifetime of nodes by pre-determined node deployment strategy based on defined principle [10].

Another paper focuses on Communication overhead and prolongs the networks lifetime [11]. Some other papers considered energy efficiency and packet delay as another major problem of a lifetime [12, 13, and 14]. Some paper considering battery of nodes focused on the challenge of designing nodes connection [15–17].

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In this paper, we want to solve the lifetime of problem of nodes by using genetic algorithm, by proposing a new function then using RDPTA technique to select priority cluster head. Simulation result shows that the proposed algorithm is relatively better than leach and leach-c algorithms, as well as the proposed algorithm has potential for inserting a new node and adapt to determinate cluster head with close node.

2. Genetic Algorithm

Genetic algorithms from Darwin's principle of natural selection to find the optimum formula to predict or to use pattern matching [6]. Genetic algorithms are often a good option for prediction techniques are based on regression. Many of the standard genetic algorithm are used to model problems [7]. Another method, genetic algorithm is used to provide energy efficient in the wireless networks as well [4]. We have described proposed genetic algorithm with new function (GA-CL) in this part that helps us to solve the lifetime of wireless sensor networks. By running the algorithm is obtained in the space as locally result.

2.1. Find the Number of Clusters

Firstly, the proposed algorithm obtains the variance values of the attributes of each object. Secondly, the variance of the values of each object obtains Standard deviation of the overall variance of the objects, that be guessed the position of objects in space. Number of clusters on the overall standard deviation is calculated. After selecting the number of clusters, we need to know what method of operator to use genetic clustering. Variance formula is as follows.

$$S^2 = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{X_i} - \bar{x})}{(\mathrm{n}-1)} \tag{1}$$

Where each X (i) be subtracted the average value of objects. And, then using the formula SD (2). Here, X (i) is the amount of the overall variance of each object.

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{x})^2}{(n-1)}} \tag{2}$$

The results of the tests literately that we've done with a rate of 0.01. For example, if s is larger than the rate, clustering is performed with the three variables otherwise below the two variables is done. Proposed rates are in the range of 0.5. If the standard deviation is between 0.01 and 0.5, it is done with a two-variable clustering procedure otherwise between 0.5 and 1 clustering is done with three variables. In fact, the ratio of the standard deviation is large which estimates the number of proper clusters.

2.2. Calculate the Evaluation Function

Here, each attribute of objects are compared with the variable and after we will be obtained a minimum fitness function. Each object is marked by the variable k with k-dimensional vector. Our goal is to minimize the obtained value of variables by comparison of object within the cluster. Let be {si |i = 1, 2... N} the number N is a set and that condition is only objects within a cluster. Firstly, by production of chromosomes divided into three parts (using the variance rate) is performed that each part is subtracted by object attributes. And, the second power provide, these are then in total and the square root is calculated (Euclid distance). And, this is done for each object, finally, the evaluation function value is obtained. Function evaluation is shown below.

$$f = \sum_{r=1}^{R} min \sum_{i=1}^{N}\sum_{j=1}^{M} \sqrt{\left(S_i - X_j\right)^2} + (\frac{en_S}{\bar{s}} / \frac{en_X}{\bar{X}}) \tag{3}$$

S attribute desired here, X is variable, r is the object, N is the number of attributes, M is the number of variables, and R is the number of objects. The relative difference of coefficient of variation of an object with coefficient of variation of chromosome of produce is calculated, which means how much value less achieved in any difference of that. Cluster centers of the visual field data points are covered optional. en_S is the standard deviation of each object. And $\bar{s}$ is the average of each object. en_X is SD of production random variable. $\bar{X}$ average of production random variable.

2.2.1. Genetic stages

The operation, in order to verify the performance has been done on the iris data set standard. And, using dunn index [8] has compared with the genetic operators. So, we implement the best operator.

2.2.2. Election

In this paper, we use the roulette wheel method. This choice has been first proposed by Holland. Probability corresponding to each chromosome, it is calculated based on fitness, If f_k is the fitness of chromosomes k. Corresponding survival probability of the chromosome is:

$$p_k = \frac{f_k}{\sum_{i=1}^{n} f_i} \quad (4)$$

Chromosomes are arranged according p_k. And, cumulative amounts p_k the same q_k that is obtained as follows:

$$q_k = \sum_i^k p_i \quad (5)$$

For each chromosome, a random number between one and zero for the number that was generated, corresponding chromosome is selected.

2.2.3. Crossover

After selecting chromosomes, the space of objects is defined by crossover steps should be taken to high value since we need the best solution in each time running. Different methods of crossover exist, such as one point, two points, Arithmetic, heuristic, scattered and intermediate tests. Crossover operators conducted on space of objects with different methods as mentioned above, and also with the total value and average value of Dunn index that is shown in the Table 1 related to rate of methods in crossover with 1000 population and Fig 1 related to the diagram of that. Finally, scattered method with 0.9 is chosen in range of 0:0.1:1 at experiments.

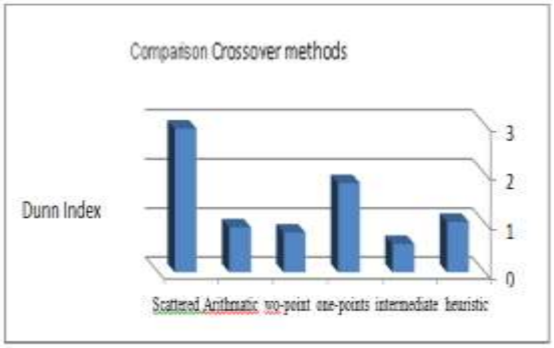

Fig. 1: Comparison of crossover od chart.

2.2.4. Mutation

In this phase, different methods are mutation uniform, mutation adapt feasible and mutation Gaussian. In order to overcome the local optimization problem is used by mutation adapt feasible implementation. By running over three times on the space of objects, the values obtained in Fig 2 is specified the number of clusters, amounts of noise and Dunn index with regard to 1000 population and 0.9 rate crossover and 1 rate mutation. (Table 2 is shown)

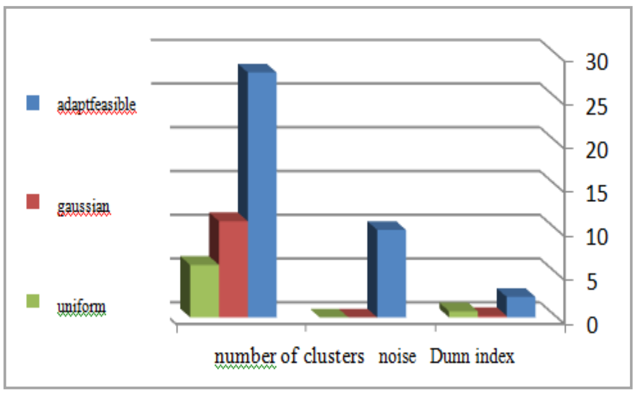

Fig. 2: Comparison of Mutation.

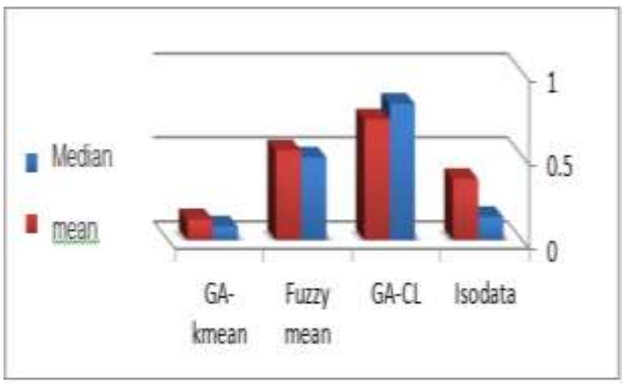

Fig. 3: Median and mean of Clustering validation.

TABLE I: Comparison of crossover of table

Operation crossover	Best fitness	Third cluster	Second cluster	First clustering	Mean
heuristic	2.22076	0.67394	1.0.2762	0.5192	4.56815
scattered	2.25608	0.81186	0.58516	0.85906	4.6161
intermediate	**2.21478**	**0.68534**	**1.01618**	**0.15326**	**4.406**
Arithmetic	2.44008	0.63928	1.22884	0.57196	4.9742
one points	2.37768	0.56998	0.6186	1.1891	4.84275
two point	2.38594	0.63302	0.85208	0.90084	4.9223

TABLE II: Compare rates on the method adapt feasible

Rate	Number of clusters	dunn index
0.1	9	0.4144
0.2	9	0.6975
0.3	14	0.7439
0.4	10	0.1107
0.5	10	1.0939
0.6	9	0.1151
0.7	9	0.0769
0.8	10	0.8814
0.9	**9**	**1.417**
1	9	0.0348

3. Comparison of Results Proposed Genetic Algorithm

In this section the proposed algorithm compares with ISO data, Fuzzy mean and GKA algorithms. Each of these algorithms on based iris data set is done by running ten times. Clustering algorithms Fuzzy mean operation has initialized. But ISO data and GKA genetic method have proposed to automatically. Fig 3 shows the validity of the algorithms on the base Dunn index.

4. RDPTA

During last year, almost study focus on neural network that inspired from the brain's model in order to improve to learning algorithm in during running. In this paper, we use one of the artificial neural system methods that's name is RDPTA. The R-Category Discrete Perception Training algorithm (RDPTA) formulate as given below. Local representation is assumed, thus indicating that R individual TLU elements are used by this R-category classifier [9].

Given are P training pairs

$\{x_1, d_1, x_2, d_2, \ldots, x_p, d_p\}$,

Where x_i is ($n\times 1$), d_i is ($R\times 1$), i=1,2,...,P . Note that augmented input vectors are used:

$$y_i=\begin{bmatrix} x_i \\ -1 \end{bmatrix}, \qquad \text{for } i=1,2,...,p \tag{6}$$

And k denotes the training step; p denotes step counter within the training cycle.

This algorithm has two formulas such as:

1- Weighted are updated

$$W_i \leftarrow W_i + \frac{1}{2}c(d_i - o_i)y, \quad for\ i = 1,2,\ldots,R \tag{7}$$

2- Cycle error is computed

$$E \leftarrow \frac{1}{2}(d_i - o_i)^2 + E, for\ i = 1,2,\ldots,R \tag{8}$$

Here, where w_i is the i'th row of Weights and where o_i the i'th row of output computer is.

This method is performed after the genetic algorithm.

4.1. Simulation

We have two phases in the simulation on our problem. As we noted, in order to solve lifetime of the wireless sensor network. Firstly, we run the genetic algorithm with new function.

4.1.1 Running genetic algorithm

We assume to have 100 nodes in environment and we want to cluster this node. After the running algorithm, our nodes are clustered based on specified variance that is shown in Fig 4.

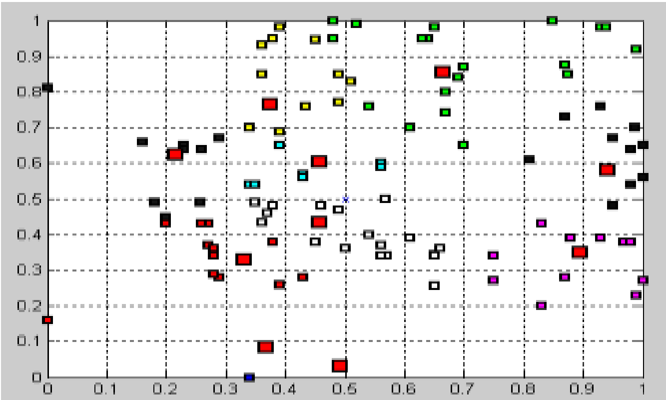

Fig. 4: Genetic algorithm performs on the nodes.

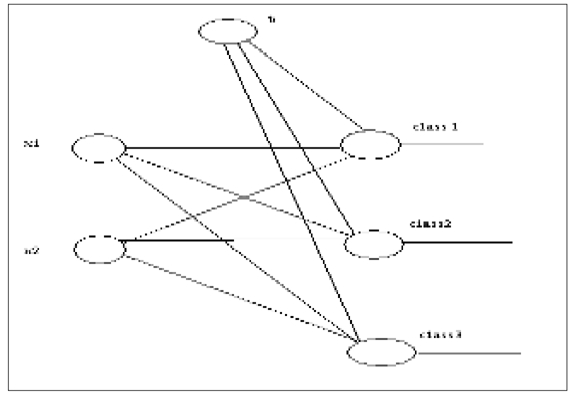

Fig. 5: Diagram for learning.

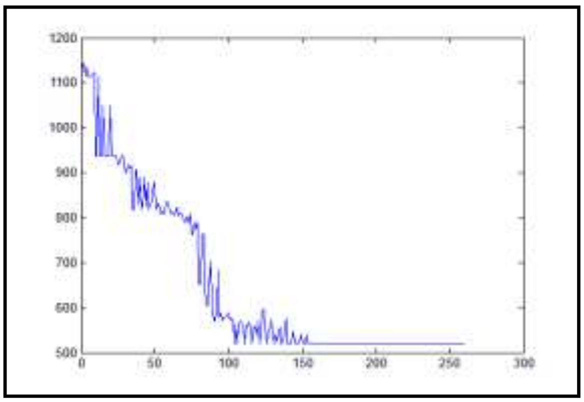

Fig. 6: Divergence of proposes algorithm

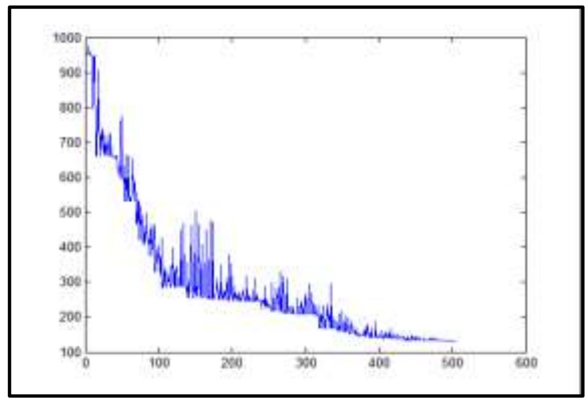

Fig. 7: Divergence of Kmeans-genetic algorithm

After the genetic algorithm we focus on the RDPTA algorithm, which has the following parameters.

Parameters used for the simulation results:

N=100, where n is the total no of nodes

P=0.2, probability of a node to become cluster head

Eo=0.5, initial energy of the nodes

ETX=50*0.000000001, transmission energy

ERX=50*0.000000001, receiving energy

Efs=10*0.000000000001 forwarding energy

Rmax=4000, maximum no. of rounds.

In this algorithm, firstly we have drawn diagram for neural system, which is specified per obtained part by the genetic algorithm. The diagram shown in the Fig 5.The proposed algorithm and genetic algorithm based on Kmean comparisons have done. The proposed algorithm Fig 6 generation production during the process of problem solving and also Fig 7 shows genetic algorithm based on Kmean (Euclidian distance). As you can see, the generation of the well and the rise of global generations to optimize the use of the genetic flexibility is better than Kmeans-genetic algorithm. In here, x_1 and x_2 are related to the Energy and Distance of nodes. Class 1, 2 and 3 are related to the rank of good-selected cluster head names as excellent and good, bad as respectively. The b is the augmented value which is related to avoiding stuck in local minimum. Secondly, we should determine about how many learning nodes per obtained part nodes by genetic algorithm. In here, we assume two nodes in this project. Two nodes are related to the priority cluster head. In this project we have defined three group priority for per obtained cluster by genetic algorithm. This step is shown in Fig 8.

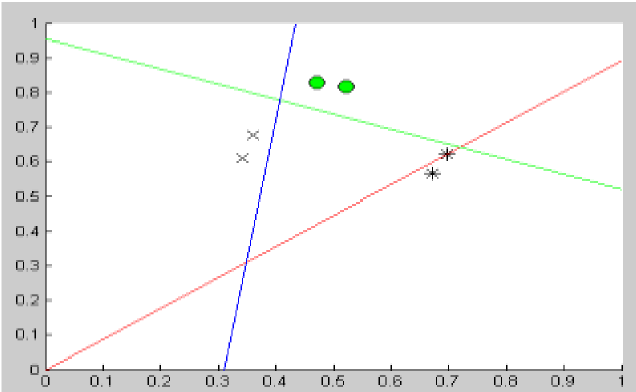

Fig. 8: Learning for each obtained part.

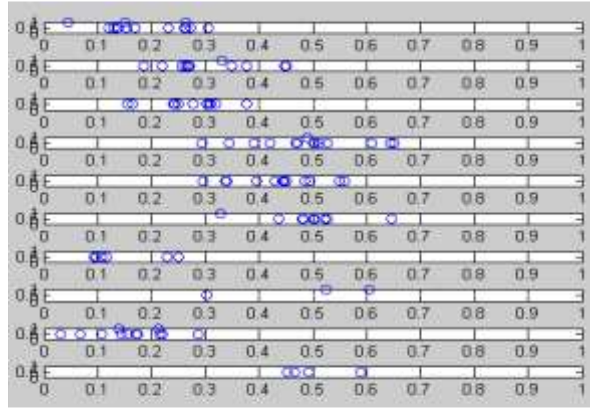

Fig. 9: Summarized figure.

This learning performs on the ten obtained parts, in during performs we can see the guide summarized figure from a hundred nodes for learning nodes. The summarized figure is shown in the fig 9.

4.2. Result of simulation

After bringing about two steps later, this algorithm has been compared with two leach and leach-c algorithms by the same parameter.

The comparison was done through using of three metrics: 1-First death time. 2-Half death time 3-Last death time. These metrics shown in the following as respectively.

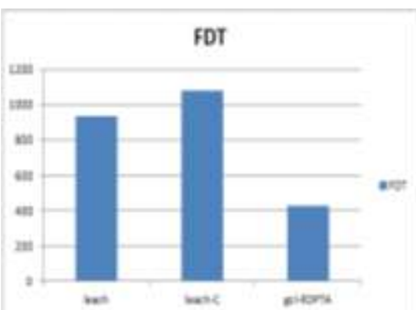

Fig. 10: First death time.

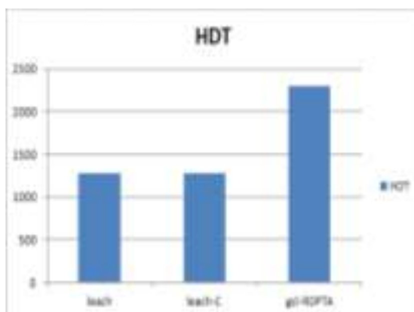

Fig. 11: Half death time.

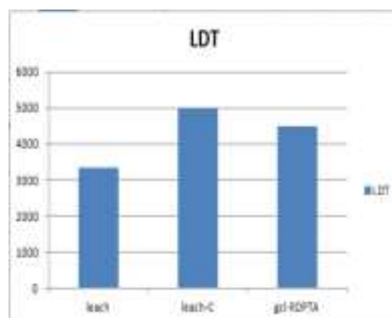

Fig. 12: Last death time.

The proposed algorithm is worse than others in the FDT metric Fig 10 but it is better than the others in the HDT metric Fig 11 as well as the proposed algorithm perform relatively well in the LDT Fig 12 This algorithm has an advantage and disadvantage. It is written in the following.

A. Advantage

1- The lifetime of proposed algorithm is better than leach and leach-c algorithms in half death time and last death time.
2- The proposed algorithm is adapted to decision making or learning nodes.
3- The proposed algorithm appropriate where in exchangeable nodes accessibly.
4-We don't need to re-cluster that decrease overload of running the algorithm,

B. Disadvantage

1- The lifetime of proposed algorithm is worse than other algorithm.
2- The proposed algorithm is low performance during the time that nodes dead simultaneously.
3- The proposed algorithm is inefficient in the very sensitive environment.

5. Conclusion

As we have observed the proposed algorithm in experience, it is relatively good, but the proposed algorithm has more flexibility than the other algorithms because it has decision-making in each part in order to how to select a cluster head and accurate control on the environment. We have tested different operators with different parameters so that by considering Dunn index on the running with 1000 population and 0.9 rate crossover and 1 rate mutation we obtained the best answer for the problem. By using the genetic algorithm and proposed new fitness with different operator in order to obtain a best solution as well as connect to the neural network technique we obtain a new insight in those for solving clustering problem.

This algorithm can be adapted with different parameter in step of the learning nodes, parameters such as:

1- Distance of a node to the center of the obtained part.

2- Approximation a node based on the previously selected nodes in the obtained part as well as these parameters are performed in n-dimensional space.

3- Instead of the proposed algorithm can be performed at non-linear a method which is very strong for solving clustering.

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